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Socio-cognitively inspired ant colony optimization

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ABSTRACT

Recently we proposed an application of ant colony optimization (ACO) to simulate socio-cognitive features of a population, incorporating perspective-taking ability to generate differently acting ant colonies. Although our main goal was simulation, we took advantage of the fact that the quality of the constructed system was evaluated based on selected traveling salesman problem instances, and the resulting computing system became a metaheuristic, which turned out to be a promising method for solving discrete problems. In this paper, we extend the initial sets of populations driven by different perspective-taking inspirations, seeking both optimal configuration for solving a number of TSP benchmarks, at the same time constituting a tool for analyzing socio-cognitive features of the individuals involved. The proposed algorithms are compared against classic ACO, and are found to prevail in most of the benchmark functions tested.

1. Introduction

Recently, there has been an increase of synergistic interaction between biological and cognitive systems on one hand, and computational systems on the other. A number of metaphors inspired from natural systems (ant colonies, bird flocks, bee swarms, and so on) have become bases for constructing interesting metaheuristics and new optimization techniques, thereby affecting the field of computing. As long as the metaheuristics are not merely relabeling terms in existing algorithms [33], they can sometimes lead to novel approaches that outperform classic metaheuristics.

In multi-agent computing systems, it has been found that different micro-level interactions of individuals in a large group often result in unexpected macro phenomena. In our project, we are applying a concept from socio-cognitive research, namely "perspective taking", which reflects the extent to which an agent is able to incorporate and be influenced by the points of view of other agents, to explore if it results in novel optimization algorithms for classic problems (in this case ant colony optimization, ACO).

An ability to view a situation from another individual's perspective is thought to be a crucial socio-cognitive characteristic for successful social interactions. This allows people to understand and predict other individuals' behaviors, and also helps them to connect emotionally with others. People, however, are not all equally skilled at perspective-taking [1], and contextual factors (e.g. emotional state) also influence how efficiently they use these skills at a given moment [5,37], and the extent to which they use these skills for a pro-social motive [18,22]. Social interactions, thus, usually involve people with diverse levels of efficiency and motivation engaging in perspective taking.

If a model can be constructed showing how perspective taking influences individuals' behaviors in a society, and how macro-level social phenomena emerge from the interaction of people with different levels of perspective taking, it can help us understand why some societies seem harmonious whereas others are ridden with conflict; it would also be useful to devise strategies to reduce conflicts. Moreover, these models, as our preliminary results suggest [32], may also help in developing new optimization strategies for traditional computational problems: for example in increasing the diversity of search for better exploration of the

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search space (similar to introducing islands into evolutionary computing methods). The current study addresses the latter issue.

Optimization heuristics, particularly these biologically-inspired techniques, have been gaining attention, for over three decades. Such approaches are supposed to be universal, though critics point to higher computation time and larger complexity of the algorithms. However, when facing difficult problems, it is usually effective to switch from deterministic approaches to stochastic search and optimization methods [36], which may justify additional costs.

Ant systems are a popular tool for solving many discrete optimization problems, e.g. traveling salesman problem (TSP), vehicle routing problem (VRP), graph coloring problem (GCP), quadratic assignment problem (QAD), and others [15]. In this article, we present the ant system as a way to express socio-cognitive behaviors of a population of ants by introducing various ant species embodying different behaviors from the point of view of their stigmergic interactions. The work presented here substantially extends our earlier research presented in [32].

Although our first goal was simulation of perspective taking during decision making using ACO as a case study, and optimization was only an example of the system application. However, as we progressed, the decision making in this case naturally became dependent on choosing the optimal path by the ants. Based on the simulation results, we discovered that an interesting optimization metaheuristic may be constructed by dividing the ants into different species, and making them interact stigmergically based on the levels of pheromone and attractivity.

This paper presents our exploration of this metaheuristics with a case study. We consider profiling of different socio-cognitively inspired metaheuristic using TSP (from the well-known TSPLIB library). Our study shows the efficiency of different variants of socio-cognitive ACO, and point to future research in this field.

After this introduction, we describe selected variants of ACO systems (Section 2), followed by socio-cognitive aspects relevant for simulations (Section 3). Next, their incorporation into ACO system is described (Section 4). Finally, experimental results are presented and discussed (Section 5), followed by conclusions (Section 6).

2. Ant colony optimization: classic and novel approaches

Ant system, introduced in 1991 by Marco Dorigo, applied to solve graph problems, is a progenitor of all ant colony optimization (ACO) techniques [13]. The classic ACO algorithm is an iterative process during which certain number of agents (ants) create a solution step by step [14,15]. The main goal of the ants is to traverse the graph finding the path with the lowest cost (usually the shortest distance, but can also be least fuel consumption, and so on).

Each step of any particular ant consists in choosing a subsequent component of the solution (that is a graph edge) with certain probability. This decision may be affected by interaction among the ants based on the levels of *pheromones*, which may be deposited into the environment (on the edges of the graph) by some ants and perceived by other ants (representing so-called attractiveness for the observed edges in order to choose the next step). This interaction is guided by stigmergic relations (communication among individuals by the means of environment, instead of direct contact directly) according to the rules proposed in [13]). The computation is finished when a feasible solution is found due to the cooperative efforts of all the ants.

There exist a number of different modifications of the classic ACO. One of them is very relevant for our study, namely multi-type ACO [29,35], which defines many species of ants and makes possible complex stigmergic interactions among them such as attraction and repulsion to/from the pheromone of different ant species. These algorithms have been successfully applied to such problems as edge disjoint path finding [29] and protection of light path [35].

Table 1
Comparison of classic ant colony optimization and socio-cognitively inspired ant colony optimization approaches.

	ACO	Socio-cognitive ACO
Species	One	Many
Pheromone table	Single common pheromone type	One pheromone type per each of species
Path attractiveness	Depending on both: pheromone and path length	Specific for each of species, may depend on pheromone and/or path length
Perception	Ants are perceived equally, pheromone of each ant has the same weight	Ants are perceived differently by other types of ant (depending on its species)

There are many more modifications of the classic ACO, such as hierarchical ACO, where additional means of control are used to manage the output of ant species [31]. Another approach assumes that ants are equipped with different skills (such as sight or speed) in order to realize global path-planning for a mobile robot [27]. Yet another, very effective, ant-based TSP solver is based on using two types of ants, classic and exploratory, and works by creating so-called “shortcuts” for the ants to move according to some predefined conditions like keep close to some selected cities. [20]. In [9], the authors introduce different ant sensitivity to pheromones such that the ants with higher sensitivity follow stronger pheromone trails, while ants with lower sensitivity behave more randomly: together, they strive to maintain a desired balance between exploration and exploitation.

The approach presented in this paper follows the results shown in [32] and the inspirations presented by Nowé et al. [29] as well as by Chira et al. [9]. We introduce different ant species and vary their sensitivity to the pheromones of the other ant species (summarized in Table 1).

3. Incorporating social and cognitive aspects

In cognitive psychology, the character traits of egocentrism (taking one’s own perspective) and altercentrism (taking another person’s perspective into consideration) have long been recognized to play a key role in interpersonal relationships (see, for instance, [16,28]). Moreover, brain-imaging studies have shown that altercentricity and the strategy of perspective taking develop in parallel with brain maturation and psychosocial development during adolescence [3,10]. Perhaps mirroring this psychological development, in recent years, artificial intelligence researchers have started to incorporate altercentricity into robots and autonomous systems [21]. We also continue with utilizing the notions of ego- and altercentrism, adapting them appropriately to use in our computing system.

Typically, perspective taking is seen as a one-dimensional ability: the degree to which an agent can take another one’s perspective. But recent research has explored a two-dimensional approach [4], where one distinguishes between the ability of an agent to handle conflict between its own and the other agent’s perspectives, and the relative priority that an agent gives to his own perspective relative to the other’s perspective. During social interactions, humans do not always share the same views. Being able to consider the other person’s point of view therefore requires putting aside one’s own perspective. This is particularly hard if one holds a strong view. Individuals endowed with good cognitive skills to manage conflicting information are therefore usually better perspective-takers [17]. In addition, however, humans also differ in terms of how much they are interested in or are willing to pay attention to others compared to themselves. Sometimes individuals focus only on their own perspective (egocentrism) while on other occasions individuals focus more on other people's perspective (altercentrism) [16,21].

The less a person focuses on her own perspective, the more that person will be motivated to engage in perspective taking [4]. Experimental research has suggested that these two dimensions (conflict handling and perspective priority) might be independent; and factors such as guilt or shame affect each of these dimensions individually [5]. This two-dimensional approach to perspective taking inspired us to define four types of individuals:

- Egocentric individuals, focusing on their own perspective and becoming creative thanks to finding their own new solutions to a given task. These individuals do not pay attention to the other ones and do not get inspired by the actions of other ones (or these inspirations do not become a main factor of their work).
- Altercentric individuals, focusing on the perspective of others and thus following the mass of others. Such individuals become less creative but they still can end up supporting good solutions by simply following them.
- Good-at-conflict-handling individuals, getting inspired in a complex way by the actions of other individuals, considering different perspectives and choosing the one considered as the best for them.
- Bad-at-conflict-handling individuals, acting purely randomly, following sometimes one perspective, sometimes another without any inner logic.

In recent work, it has been shown that the proportion of altercentric, egocentric, good and bad perspective conflict handlers can fluctuate within humans depending on situational factors (reference). In our first set of simulations, we choose as starting point three types of proportions found in humans: one representing the proportion of perspective-taking profiles in a baseline condition (without manipulation of situational factors), and two types of proportions corresponding to the effects of two situational factors, namely guilt and anger. These two factors affect perspective taking in opposing ways: guilt heightens and anger lowers the proportion of altercentric individuals [5]:

- Control sample (baseline proportions of different types of perspective takers found in a typical human population), where good conflict handlers form a major proportion with a roughly similar proportion of the three other types of perspective takers. It is to note that this is also the sample with the highest proportion of egocentric individuals.
- Increased good conflict handling sample (proportions based on a population of humans which has been induced to feel anger) where proportion of good conflict handlers is further increased compared to the control sample, while reducing the fraction of the altercentric and egocentric individuals.
- Increased altercentricity sample (proportions based on a population of humans which has been induced to feel guilt), where the proportion of good conflict handlers and egocentric individuals is significantly decreased and is compensated by a higher proportion of altercentric individuals and to a lesser extent a higher proportion of bad conflict handlers.

In a second set of simulations, we varied in a more systematic way the proportions of types of individuals to examine their respective efficiency in finding a solution.

4. Socio-cognitive ant colony optimization

Starting from the definition of classic ACO, the problem of combinatorial optimization is considered (e.g. to find the shortest cycle (Hamiltonian) in a graph as in travelling salesman problem). This method is based on moving the individuals, so-called ants, that along the edges of a graph, searching for different cycles and secreting trails of pheromones behind them.

4.1. Classic ACO

In the classic ACO algorithm, the individuals (ants) are deployed in a graph consisting of a set of vertices $V = i, j, \ldots; i, j \in \mathbb{N}$ and a set of edges E. It is to note, that each edge is associated with certain distance. Each ant gets a randomly chosen starting graph node, and searches for a cycle, by moving between the nodes (always choosing the next one, never coming back). While choosing which node to visit next, the ant has to evaluate the attractiveness factor for all possible edges that can be followed from the present node. The attractiveness n_{ij} of the edge ij starting from the node i where the ant is currently at is the basis for computing the probability of choosing a particular path:

$$\mu_{ij} = \frac{n_{ij}}{\sum_j n_{ij}} \tag{1}$$

where j is computed only for nodes that have not yet been visited by the ant.

The actual values of n_{ij}, which is the attractiveness computed for the next edges considered as potential next steps in the constructed path in the case of classic ants and all the proposed modifications discussed below.

Finally, the ant randomly selects a path based on the previously computed probabilities: the paths with higher attractiveness are more likely to be chosen. After visiting all the nodes exactly once, the ant finishes its trip and returns the found cycle as a proposed solution, and then retreats depositing certain amount of pheromone on the path of its current cycle. The amount of pheromone deposited on an edge e_{ij} is denoted by π_{ij}, and the deposition algorithm of ant a_k retreating along cycle c_{a_k} is the following:

$$\pi'_{ij} \leftarrow \pi_{ij} + \frac{\pi_d}{\sum_{e \in c_{a_k}} dist(e)} \tag{2}$$

where the default pheromone deposit π_d is 1, x' refers to the updated value of x, e_{ij} denotes an edge in the cycle, and $dist(e_{ij}) : E \to \mathbb{R}$ is a function that returns a distance of each edge.

It is to note, that the pheromone evaporates in each iteration (in each edge of the graph) according to this formula:

$$\pi'_{ij} = (1 - \pi_e) \cdot \pi_{ij} \tag{3}$$

A default pheromone evaporation coefficient π_e is 0.01.

4.1.1. Classic ants

These ants consider both pheromone and distance while choosing their direction by computing *path attractiveness* in order to complete the cycle. In this case, an ant present at a node i will choose the next edge according to the following attractiveness:

$$n_{ij} = \frac{\pi_{ij}^{\alpha}}{dist(e_{ij})^{\beta}} \tag{4}$$

Default factors are, pheromone influence $\alpha = 2.0$, distance influence $\beta = 3.0$.

Each type of ant described in Section 4.2 uses Eq. (1) to calculate probabilities for the subsequently chosen edges, differing only in attractiveness to various types of pheromones.

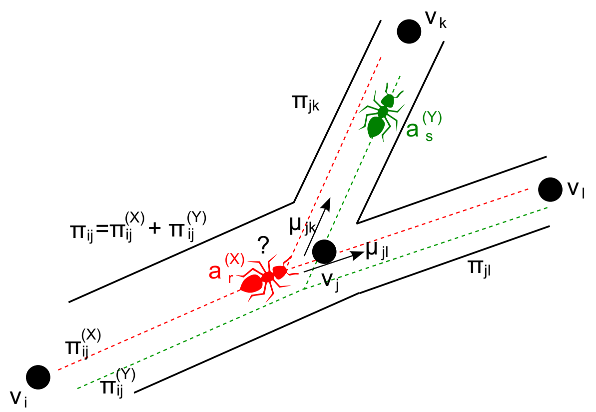


Fig. 1. Multi-pheromone ACO setting: different species of ants leave different pheromones, but the ants may decide based not only by the pheromone of its species, but also combining the information about other ones. In this case the red ant decides on taking the path based on red and green species pheromones. (For interpretation of the references to color in this legend, the reader is referred to the web version of the article.)

4.2. Multi-pheromone ACO

In the proposed socio-cognitive ACO, the idea of having many pheromones instead of only one is implemented by introducing different "species" of ants and enabling their interactions (similar to the approach taken in [29]). The interaction is considered as a partial inspiration (similar to perspective taking in a real world), realized by a particular ant reacting to the decisions taken by ants belonging to other species. This is made possible by having ants of different species leave different "smells" (see Fig. 1).

Different ants follow different rules (i.e. they consider different properties of the path) of computing the attractiveness factor. They utilize the smells of pheromones left by other species in a predefined way.

Different ant species leave pheromones that 'smell' different, so the pheromone left at a particular edge is described in the following way:

$$\pi_{ij}=\pi_{ij}^{(EC)}+\pi_{ij}^{(AC)}+\pi_{ij}^{(GC)}+\pi_{ij}^{(BC)} \tag{5}$$

where the classic pheromone π_{ij} for the particular edge is computed as a simple sum of different pheromones deposited by other species on this edge.

Other ants may react to different combinations of these pheromones. Of course, more species and more pheromones may be introduced into the system if necessary.

Based on this framework, details of the actions undertaken by various ant species are described below. It is to note, that the chosen species, namely egocentric, altercentric, good- and bad-at conflict handling were chosen based on the real-world features of the human population (based on the suggestions of one of the co-authors).

4.2.1. Egocentric ants (EC)

These ants are supposed to be creative in trying to find a new solution. They care less about other ants and about the pheromone trail. Instead, they focus mostly on the distance of traveling of the path as a way to determine their next directions. An ant at node i will choose the next edge with the attractiveness computed as follows:

$$n_{ij}=\frac{1}{dist(e_{ij})^{\beta}} \tag{6}$$

The default distance influence β = 3.0, again.

4.2.2. Altercentric ants (AC)

These ants follow the majority of other ones, focusing on the pheromone, without caring for the distance. So an ant at node i will choose the next edge with the following attractiveness:

$$n_{ij}=\pi_{ij}^{\alpha} \tag{7}$$

Default pheromone influence α = 2.0.

4.2.3. Good-at-conflict-handling ants (GC)

These ants observe the others, caring for all existing pheromones (the particular weights are to be determined experimentally). So an ant at node i will choose the next edge with the following attractiveness:

$$n_{ij}=\left(14\cdot\pi_{ij}^{(EC)}+2\cdot\pi_{ij}^{(AC)}+2.5\cdot\pi_{ij}^{(GC)}+0.5\cdot\pi_{ij}^{(BC)}\right)^{\alpha} \tag{8}$$

Default pheromone influence α = 2.0.

The values assumed for the distance influence β, pheromone influence α and influences of the particular parts of the pheromones on the attractiveness perceived by the GC ant were obtained experimentally, and confirmed after already being used in two publications [32,34]. In the future these values are planned to be properly reconfirmed and a relevant publication is envisaged.

4.2.4. Bad-at-conflict-handling ants (BC)

These ants behave randomly, irrespective of the pheromone or the distance. So an ant at node i will choose the next edge with the following attractiveness:

$$n_{ij}=\frac{1}{\sum_{e_{ik},k\in V\setminus\{i\}}} \tag{9}$$

5. Experimental results

The experimental results were obtained from a dedicated software developed in Python,[1] run on Zeus supercomputer.[2] We considered the travelling salesman problem: find a Hamiltonian in a graph defined by a network of cities, with the goal being a cycle with the least cost (distance) [19]. The instances used in the experiments were taken from TSPLIB library.[3]

5.1. Configuration and infrastructure

Zeus cluster, which is a supercomputer consisting of different kinds of 2-processor servers with different processor frequencies, number of cores, number of cores per node and RAM memory per node. Experiments were run on machine with the following technical parameters: Model: HP BL2x220c G5, G6, G7, Total number of cores: 17,516, Processors: 2x Intel Xeon L5420, L5640, X5650, E5645, Number of cores per node: 8–12, Processor frequency: 2.26–2.66 GHz, RAM memory per node: 16–24 GB.

The following platform configuration was assumed for each experimental run:

- Number of ants: 100.
- Number of iterations (in order): 20, 50, 100.
- Number of trials for each experiment: 30. Final data is the average of these 30 trials.
- Tested data taken from TSPLIB: berlin52, eil51, kroB200, eil76, kroA100, kroE100, pr76, st70, lin105, rat195, ts225, pr264.

[1] www.python.org
[2] http://plgrid.pl
[3] http://www.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/

During the experiment, the following compositions (with respect to proportions of different ant species) of the simulated population were considered:

- Classic Ant Population **(ca)**: Only ants acting as in classic ACO.
- Human-inspired sample populations:
  - Control Sample Population **(humControl)**: 22% egocentric, 15% altercentric, 45% good at conflict handling, 18% bad at conflict handling.
  - Increased Altercentricity Sample Population **(humAlter)**: 3% egocentric, 46% altercentric, 23% good at conflict handling, 28% bad at conflict handling.
  - Increased Good Conflict Handling Sample Population **(humGood)**: 6% egocentric, 6% altercentric, 63% good at conflict handling, 25% bad at conflict handling.
- Modifications based on human-inspired sample populations:
  - Equal **(eq)** population: 25% egocentric, 25% altercentric, 25% good at conflict handling, 25% bad at conflict handling.
  - Equal without bad at conflict handling **(eqWithoutBad)** population: 34% egocentric, 33% altercentric, 33% good at conflict handling, 0% bad at conflict handling.
  - Egocentrical **(ego)** population: 55% egocentric, 15% altercentric, 15% good at conflict handling, 15% bad at conflict handling.
  - Egocentrical without bad at conflict handling **(egoWithoutBad)** population: 60% egocentric, 20% altercentric, 20% good at conflict handling, 0% bad at conflict handling.
  - Altercentrical **(alter)** population: 15% egocentric, 55% altercentric, 15% good at conflict handling, 15% bad at conflict handling.
  - Altercentrical without bad at conflict handling **(alterWithoutBad)** population: 20% egocentric, 60% altercentric, 20% good at conflict handling, 0% bad at conflict handling.
  - Good at conflict handling **(good)** population: 15% egocentric, 15% altercentric, 55% good at conflict handling, 15% bad at conflict handling.
  - Good at conflict handling without bad at conflict handling **(goodWithoutBad)** population: 20% egocentric, 20% altercentric, 60% good at conflict handling, 0% bad at conflict handling.
- Homogeneous populations (in order to check the extent of the species synergy):
  - 100% egocentric.
  - 100% altercentric.
  - 100% good at conflict handling.
  - 100% bad at conflict handling.

5.2. Experiment: phase 1

In the first step of the experiment, our goal was to find the most promising population configuration. We tested all the above-mentioned populations (besides the classic ACO). Three benchmarks were chosen to classify each population's effectiveness:

- eil51 (best known solution: 426)
- berlin52 (best known solution: 7542)
- kroB200 (best known solution: 29,437)

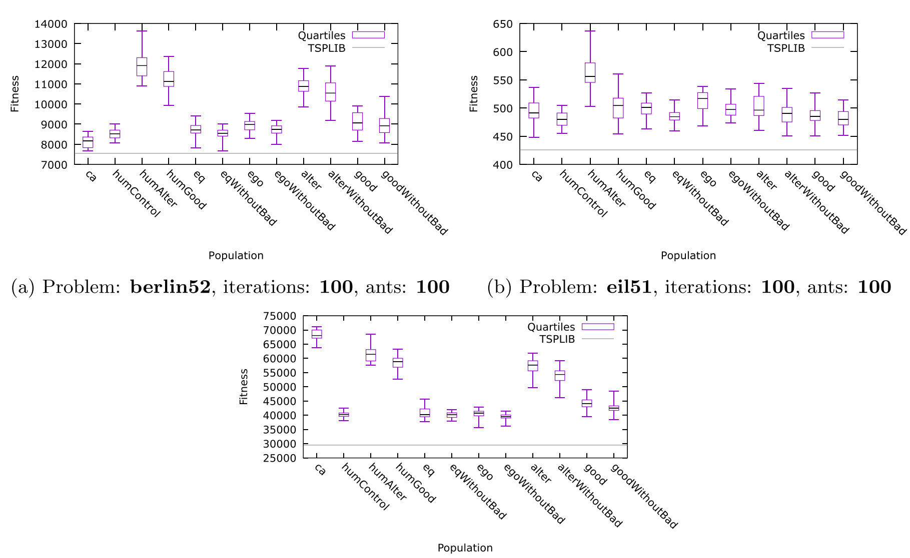
The results of our test runs are shown in Fig. 2.

After examining the graphs, it turned out that in many tested cases, configurations without bad-at-conflict-handling ants (with **"WithoutBad"** suffix in population names) got our attention as quite effective ones, thus we chose these configuration to choose the one for further examination.

Unlike small benchmarks (like eil51, see Fig. 2b), where most of the tested populations gave almost the same final results, mid-sized and big benchmarks (respectively: berlin52 (see Fig. 2a) and kroB200 (see Fig. 2c)) demonstrate clearly the low quality of certain configurations. As shown in the above figures (see Fig. 2), **egoWithoutBad** and **eqWithoutBad** configurations achieve the best fitness, but in the general summary (considering each presented charts) **egoWithoutBad** population appears to be a little better, especially when taking into consideration more complex problems, therefore this configuration will be compared with the classic ACO further in the article.

5.3. A closer look into ***egoWithoutBad*** population

In the next part of the experiment, we paid closer attention to the **egoWithoutBad** population and compared it with the classic ACO. This included comparing the final fitness score of both the populations, as well as their speed of convergence in achieving a better fitness during iterations.



(a) Problem: **berlin52**, iterations: **100**, ants: **100**

(b) Problem: **eil51**, iterations: **100**, ants: **100**

(c) Problem: **kroB200**, iterations: **100**, ants: **100**

Fig. 2. Fitness acquired in the last iteration by each of the examined populations for three tackled TSPLIB problems of different difficulty.

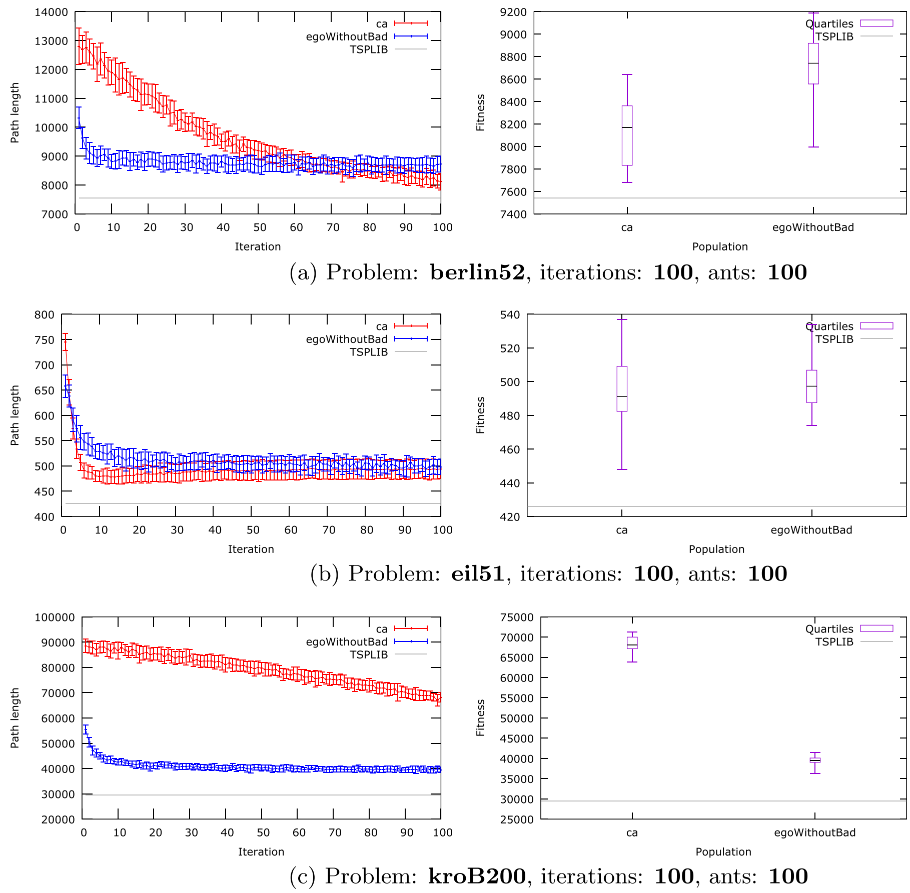


Fig. 3. Comparison of **classic ACO (ca)** and **egoWithoutBad** populations fitnesses dependent on the iteration, and in the final iteration.

These results are presented in Fig. 3.

The **egoWithoutBad** population performs at least almost as good as the classic ACO (see Fig. 3a and b), but in case of big-sized problems, it performs much better: its final fitness is much closer to the best known solution than the classic ACO (see Fig. 3c). Moreover, **egoWithoutBad** reaches better fitness much earlier than the classic ACO (approximately in the **tenth** iteration).

5.4. Homogeneous populations

The next part of the experiment was to examine the behavior of homogeneous populations (consisting of 100% ants of a single type) compared to the mixed populations listed above. The results of these experiments are presented in Fig. 4. Our goal here is to show that introducing diversity in a population indeed helps – otherwise

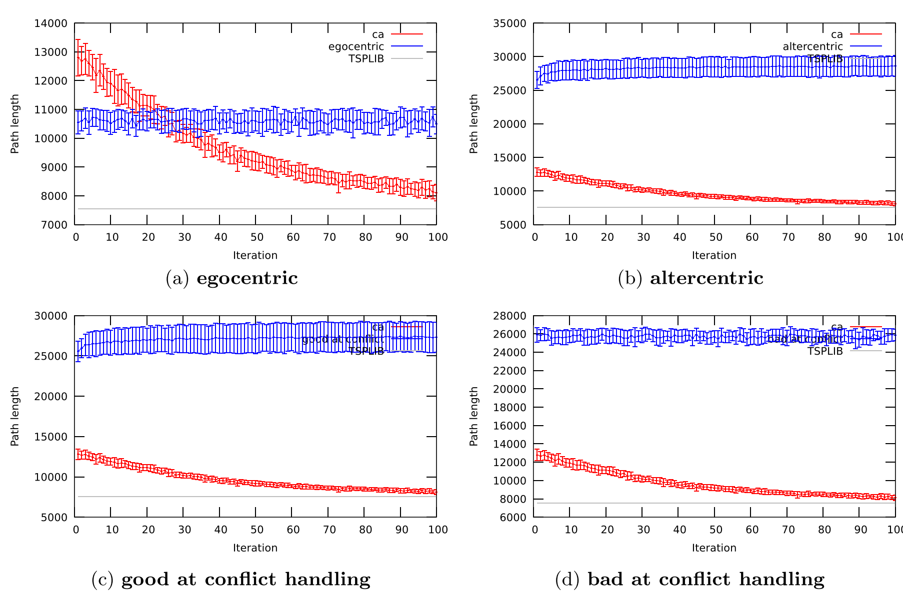


Fig. 4. Fitness of homogeneous populations compared to the classic ACO (ca).

Table 2
Summaric results for each problem comparing **egoWithoutBad** population and **classic ACO** population results (fitness, stdev, median, max, min) for sequentially: 20, 50 and 100 iterations

		20 Iterations					50 Iterations					100 Iterations					
		Fitness	Stdev	Median	Max	Min	Fitness	Stdev	Median	Max	Min	Fitness	Stdev	Median	Max	Min	Best known
eil51	ca	478.99	15.34	474.03	507.18	448.42	491.93	15.13	489.02	525.50	463.08	494.15	19.41	491.28	536.96	448.00	426
	egoWithoutBad	519.81	14.18	519.60	544.92	486.20	503.77	14.26	504.96	532.64	469.78	498.32	14.95	497.27	533.83	474.07	
berlin52	ca	11,022.72	395.41	11,039.33	11,860.66	10,048.46	9227.92	273.86	9294.71	9591.87	8336.74	8112.31	286.34	8167.93	8638.26	7677.66	7542
	egoWithoutBad	**8757.05**	272.41	8768.28	9308.77	8130.56	**8763.54**	251.13	8751.44	9211.50	8063.69	8727.56	280.27	8740.42	9187.20	7994.74	
kroB200	ca	85,493.27	2956.28	86,323.39	89,849.80	77,795.71	80,105.73	1650.93	80,400.52	83,895.09	74,989.03	68,184.50	1898.08	68,066.80	71,211.87	63,857.67	29,437
	egoWithoutBad	**41,154.82**	1048.77	41,208.18	43,309.33	38,325.23	**40,103.79**	1103.62	40,124.60	41,691.73	37,220.13	**39,455.89**	1074.52	39,483.09	41,424.30	36,239.60	
eil76	ca	592.50	12.62	593.50	614.57	570.69	595.51	14.41	594.19	625.43	569.73	603.81	15.90	600.26	631.64	574.60	538
	egoWithoutBad	678.96	22.02	682.98	707.50	616.87	657.52	17.56	661.72	689.51	619.89	645.41	13.93	644.36	673.51	618.29	
kroA100	ca	47,085.66	2260.01	47,603.09	51,202.23	41,132.88	42,392.05	1474.85	42,311.00	44,470.66	38,743.53	34,173.37	1129.09	34,235.51	36,295.30	31,460.71	21,282
	egoWithoutBad	**28,090.20**	825.43	27,962.27	29,534.12	26,268.45	**27,806.59**	618.92	27,790.66	28,842.27	26,687.32	**27,483.31**	1031.67	27,722.78	28,712.37	24,482.68	
kroE100	ca	47,821.57	1861.18	48,008.87	51,651.63	42,852.76	43,036.32	1659.95	42,967.44	46,114.04	38,046.19	34,832.45	1366.99	34,936.77	37,365.10	31,527.57	22,068
	egoWithoutBad	**28,003.67**	1029.93	27,858.90	29,650.07	25,300.71	**27,575.23**	886.45	27,617.61	29,397.30	24,976.15	**27,356.84**	905.07	27,433.92	29,395.88	25,732.59	
lin105	ca	29,315.13	1286.47	29,728.70	30,780.70	25,764.69	25,132.15	1044.82	25,262.40	27,260.30	22,900.89	20,714.70	742.19	20,793.44	22,029.58	18,956.58	14,379
	egoWithoutBad	**18,754.85**	817.75	18,956.95	19,702.29	16,295.73	**18,441.99**	745.83	18,316.22	19,780.33	17,097.03	**18,262.87**	627.62	18,159.40	19,428.89	17,044.86	
pr264	ca	134,305.60	4576.44	134,569.14	142,567.66	122,442.11	126,263.89	5120.08	126,053.25	134,602.77	113,578.57	112,541.28	3786.08	113,261.38	119,005.07	100,365.64	49,135
	egoWithoutBad	**69,494.39**	2168.02	69,514.77	76,582.62	65,531.74	**66,513.92**	2290.60	67,056.73	70,811.54	62,693.75	**66,223.05**	2009.70	66,303.07	70,026.10	62,333.61	
pr76	ca	222,716.57	6737.87	223,138.07	235,414.64	203,345.78	217,027.41	8674.34	218,211.88	233,447.09	197,292.25	200,383.26	9507.43	200,180.66	217,390.34	176,767.31	108,159
	egoWithoutBad	**133,632.58**	4922.71	133,640.96	144,252.89	122,087.23	**130,152.10**	4622.92	129,060.74	140,814.70	121,574.35	**130,319.20**	4760.09	129,943.33	142,062.52	122,624.22	
rat195	ca	4701.67	169.90	4738.26	4957.83	4310.48	2873.68	73.35	2878.64	3009.94	2689.53	2653.71	66.76	2649.12	2796.84	2481.44	2323
	egoWithoutBad	**3169.40**	121.41	3180.48	3372.08	2803.98	2990.02	89.22	3005.12	3110.63	2810.15	2899.60	60.42	2905.48	2996.09	2784.33	
st70	ca	784.60	19.09	786.52	816.61	746.81	787.86	19.38	789.60	830.98	750.53	788.41	26.62	785.89	840.36	723.01	675
	egoWithoutBad	872.87	22.98	880.16	910.50	817.82	842.41	25.01	841.32	892.36	789.38	841.68	23.56	842.31	888.89	783.94	
ts225	ca	470,165.46	14,501.94	472,284.14	492,594.79	429,026.94	462,478.86	15,553.55	466,419.57	482,509.79	422,507.27	444,967.84	15,368.94	447,311.13	478,072.14	411,809.80	126,643
	egoWithoutBad	**165,392.39**	4934.86	163,219.77	174,176.02	156,692.07	**159,771.84**	5287.88	159,871.49	169,159.16	146,695.09	**158,836.69**	4048.33	159,712.68	165,133.82	148,808.70	

concentrating on just one single species of ants would be sufficient to solve the given problems.

As expected, homogeneous populations turned out to be significantly worse than the diverse ones (see Fig. 4), which means that the strength of the algorithm lies in the synergy of different ant species.

5.5. Experiments on other benchmarks

Further experiments were conducted to test the better-performing **egoWithoutBad** population on other benchmarks: eil76 (best known solution: 538), st70 (best known solution: 675), rat195 (best known solution: 2323), lin105 (best known solution: 14,379), kroA100 (best known solution: 21,282), kroE100 (best known solution: 22,068), pr76 (best known solution: 108,159), pr264 (best known solution: 49,135), ts225 (best known solution: 126,643).

5.6. Results summary

The table (see Table 2) presents the results (fitness, stdev, median, max, min) for each problem comparing the **egoWithoutBad** population with the **classic ACO (ca)** population for 20th, 50th and 100th iteration step. The bold font indicates the cases, where the examined **egoWithoutBad** population turned out to be significantly better than the classic ACO.

6. Conclusion

Difficult problems require novel metaheuristics, so the search for new inspirations is always needed and attractive from the scientific point of view. In this paper we have shown that effective methods of computation may be conceived by observing socio-cognitive relations among individuals: this was the inspiration for the research presented here.

Surprisingly, our first research goal, namely the simulation of socio-cognitive phenomena in a population of computing ants (formulated in [32]), turned out to have an interesting side-effect, namely efficient handling of the tackled problem in certain configurations. Based on the preliminary results we have extended and enhanced the ant populations, and sought out the best suited ones for the tackled problems. We did not obtain one configuration that prevailed in all the tackled problems (cf. No Free Lunch theorem [36]), however one of them seemed to be very efficient in solving most of the problems. The prevailing population consisted of 50% egocentric ants (focused on their own knowledge) but also included altercentric and good-at-conflict-handling ones. We suppose that in this way the diversity of the ant population was enhanced, compared to the classic ACO, thereby suggesting that to employ a diverse population and perspective-taking inspirations leads to better results. This is consistent with a large body of research showing that team diversity is a key to creativity and innovation [30]. In our future research, we plan to design appropriate diversity measurement methods and monitor the diversity of the ant populations during the experiments to study how it correlates to efficiency.

We claim to have developed a new metaheuristic algorithm, extending the existing, well known ACO and our extension fits well with the existing ACO principles – as the socio-cognitive ants are implemented as multiple species with extension of perceiving of the pheromone and the attractiveness to other species. This our approach goes beyond merely attaching new labels to existing algorithms, which has come under criticism by some scholars [33].

The tested configuration of our metaheuristic prevailed in the optimization of most TSPLIB instances tested when compared to the classic ACO. But this may be further improved as follows. In our current system, we fixed the parameters of our algorithm to make it similar to the real-world psychological observations (e.g. "good at conflict handling" species structure was based on the real-world observation of human population). However, in the future, we plan to drop these direct connection with the metaphor, reflected in the parameter values, to develop the proposed metaheuristic into a more general tool, mostly utilizing multi-population and complex decision-taking process based on multiple pheromones and different perception of attractiveness. We will of course search for correct parameters of the metaheuristic when applied to particular problems. We also plan to broaden our base of competitive algorithms, not relying only on classic ACO but including some of its other modifications, like e.g. ant colony system by Dorigo [11]. We will also use the Scalarm [24,23], a data-farming environment, to facilitate the execution and analysis of the experiments.

As ant systems are example of a simple agent-based computing system, as an ant may be treated as computational agent [12], constructing its solution based on partial information available in the system by stigmergic communication with other ants. Computing agent systems are already one of main topics of authors' research, that is particularly focused on so-called evolutionary multi-agent system [8], for which theoretical models were built [7,6], and a number of efficient frameworks [26,25]. However the agency in the ACO and similar computing systems is quite limited, the authors strive to enhance this notion, both in this paper (focusing on socio-cognitive aspects and novel stigmergic communication), and in future papers by finding novel ways of enhancing agency in ant computing systems.

Besides ACO, other stigmergic or quasi-stigmergic systems as particle swarm optimization can also be considered as starting points for simulations, and one can study how incorporating socio-cognitive features might enhance their performance. We have already started this research and the initial results may be found in [2].

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